Evaluation the Effect of Machining Parameters on Mrr of Mild Steel

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Abstract— Turning metal removal is the removal of metal outside diameter of a rotating cylindrical workpiece. As it is used to reduce the diameter. of the work piece generally to a specified dimension and to produce a smooth finish on the metal. Often, the work piece is turned so that the sections have different diameters. As is the machining operation that produces cylindrical. In its basic form, it can be defined as an outer surface machining: Based on the findings of the Pilot study, actual experimentation work will be designed and input machining parameters and their values finalized. The results are expected to show that the response variables (output parameters) strongly influenced by the control factors (input parameters). So, the results which are obtained after experimentation analyzed and modeled for their application in manufacturing industry It is concluded that for MRR be maximum factor Cutting speed has to be at high level 3, Feed has to be at high level & D.O.C has to be at high level.

Key words: Taguchi Design, Orthogonal Array, Turning, Cutting Speed, Feed

I. INTRODUCTION

Kohli and Dixit (2005) [1] proposed a method based on the neural network with the acceleration of the radial vibration of the tool holder as feedback. The backpropagation algorithm is used to train the network model for predicting the surface roughness in turning process. The methodology was validated for turning dry and wet steel using high speed steel and carbide tool and noted that the proposed methodology was able to make an accurate prediction of surface roughness using small formation of size and testing data sets. Pal and Chakraborty (2005) [2] studied to develop a model of neural network back-propagation for prediction of surface roughness in turning operation and is used mild steel work pieces with high speed steel as the cutting tool to carry out a number of experiments. The authors used speed, feed, depth of cut and cutting forces as inputs to the neural network model for prediction of surface roughness. The work resulted in the intended surface roughness was very close to the experimental value.Sing and Kumar (2006) [3] studied the optimization of the feed force through optimum adjustment of process parameters namely speed, feed and depth of cut in steel processing with carbide inserts EN24 TiC coated tungsten. The authors used the approach Taguchi design parameters and concluded that the effect of feed and cutting depth variation in feed force affected more as compared to the speed. Ahmed (2006) [4] developed the methodology for obtaining the optimum process parameters for prediction of surface roughness in turning Al. To develop the empirical model nonlinear regression analysis with logarithmic transformation of data it was applied. The model developed showed little mistakes and satisfactory results. The study concluded that low feed rate was good to produce low surface roughness and high speed couldproduce high surface quality within the experimental domain. Abburi and Dixit (2006) [5] they developed based on knowledge for predicting surface roughness in turning process system. Fuzzy set theory and neural networks were used for this purpose. The authors developed rule to predict the surface roughness for the process variables as well as for the prediction of process variables for a given surface roughness. Zhong et al. (2006) [6] predicted the surface roughness of machined surfaces using nets with seven innings namely degree insertion tool, workpiece materials, cutting edge radius, angle, depth of cut, spindle speed and feed rate . Kumanan et al. (2006) [7] proposed a methodology for predicting the machining forces using multilayer perceptron trained by genetic algorithm (GA). The data obtained from experimental results of a turning process is explored to train artificial neural networks proposed (RNAs) with three inputs for output machining forces. ANN optimal weights were obtained using GA search. This hybrid function replacing made of GA and ANN found computationally efficient and accurate to predict the forces of machining for the machining conditions of entry. Mahmoud and Abdelkarim (2006) [8] studied in turning operation using high speed steel (HSS) cutting tool 450 at an angle of approach. This tool proved he could carry out the cutting operation at higher speeds and longer service life of the traditional tool with a rake angle of 90 degrees. The study ultimately determines the optimum cutting speed for high production speed and minimum cost and tool, production time and operating costs. Doniavi et al. (2007) [9] using the response surface methodology (RSM) in order to develop the empirical model for the prediction of surface roughness, in deciding the optimal cutting condition in the transformation. The authors showed that the feed rate significantly influenced surface roughness. With increased surface roughness speed power was found to be increased. With the increase in the cutting speed decreased surface roughness. Analysis of variance showed that the influence of the feed rate and were in surface roughness of the cutting depth was applied. Kassab and Khoshnaw (2007) [10] examined the correlation between surface roughness and vibration cutting tool for turning operations. The process parameters were cutting speed, depth of cut, feed rate and outstanding tool. The experiments were carried out on the lathe turning using dry (without cutting fluid) operation of medium carbon steel with different levels of process parameters mentioned above. Turning was dry useful for a good correlation between the surface roughness and the cutting tool vibration due clean environment. The authors developed a good correlation between the vibration cutting tool surface roughness and to control the surface finish of the workpieces during mass production. The study concluded that it was observed that the surface roughness of the workpiece to be affected more by the acceleration cutting tool; acceleration increased overhang of the cutting tool. The surface roughness was found to increase with increasing feed rate. Al-Ahmari (2007) [11] developed empirical models for the tool life, surface roughness and cutting force for turning operation. The process parameters were used in the study speed, feed, depth of cut and the nose radius to develop the model machining. The methods used to develop 48 models mentioned above were Response Surface Methodology (RSM) and neural networks (NN). Thamizhmanii et al. (2007) [12] applied the Taguchi method to find the optimal value of the roughness of the surface under optimal cutting conditions in turning SCM 440 alloy steel. The experiment was designed using the Taguchi method and experiments were carried out and the results thereof were analyzed with the help of ANOVA (analysis of variance). The causes of poor surface finish as vibrations were detected machine tool, tool chatter whose effects were ignored for analysis. The authors concluded that the results obtained by this method would be useful for other research study similar type of tool vibrations, forces, etc. The study concluded that cutting deppth was the only major factor that contributed to the roughness of the cutting surface. Natarajan et al. (2007) [13] introduced the technique of monitoring tool wear online processing operation. Spindle speed, feed, cutting depth, cutting force, power spindle motor and temperature were selected as the input parameters for the monitoring technique. To determine the degree of wear of the tool; Two methods of Hidden Markov Model (HMM) method such as bar-graph and multiple modeling methods were used. An algorithm of decision fusion center (DFCA) was used to increase the reliability of this output that combines the outputs of the individual methods to make a comprehensive decision on the wear of the tool. Finally, all the proposed methods were combined in a DFCA to determine the wear of the tool during turning operations. Ozel et al. (2007) [14] conducted the finish turning of steels AISI D2 (60 HRC) using ceramic (multi-radio) design inserts cleaner surface finish and tool flank wear research. For prediction of surface roughness and tool flank wear multiple linear regression models and neural network models were developed. Predictions based neural network of surface roughness and tool flank wear were carried out in comparison with a non-formation experimental data and the results thereof showed that neural network models proposed were efficient for predicting patterns tool wear and surface roughness for a range of cutting conditions. The study concluded that the best tool life was obtained in lower feed rate and the lowest shear rate combination. Wang Lan (2008) [15] using orthogonal array of Taguchi method gray relational analysis with considering four parameters viz. speed, depth, rate of cutting tool nose to drain, etc., for the optimization of three responses: surface roughness, the tool wear and material removal rate on the accuracy of light a ECOCA-3807 CNC lathe. It explored the MINITAB software to analyze the average signal-to-noise (S / N) effect to achieve the multi-purpose features. This study not only suggests an optimization approaches using orthogonal matrix and gray relational analysis, but also contributed a satisfactory technique to improve performance of multiple precision machining CNC turning, with profound insight. Srikanth and Kamala (2008) [16] evaluated the optimal values of cutting parameters using a genetic algorithm coded Real (RCGA) and various issues RCGA and its advantages over the current approach of Binary Coded Genetic Algorithm explained (BCGA). They concluded that RCGA was reliable and accurate to solve the optimization parameter and build cutting optimization problem with multiple decision variables. These decision variables were cutting speed, feed, depth of cut and nose radius. The authors noted that the fastest solution RCGA can be obtained with relatively high success rate, with selected machining conditions providing for overall improvement mode product quality by reducing the cost of production, reduction in time production, flexibility in the selection of machining parameters. Sahoo et al. (2008) [17] studied for optimization of machining parameters combinations emphasis on fractal characteristics of surface profile generated in CNC turning operation. The authors used the L27 orthogonal array design with machining Taguchi parameters: speed, feed and depth of cut in three different work piece materials viz. aluminum, mild steel and brass. It was concluded that the feed rate was more significant influence surface finish on the three materials. It was observed that in the case of mild steel and aluminum feed showed some influences, whereas in the case of brass cutting depth was noticed impose some influence on the surface finish. The interaction factor was responsible for controlling the fractal dimensions of the surface profile produced in CNC turning.

II. DESIGN OF EXPERIMENTS

Engineering methods, the quality of Dr. Taguchi hired to design experiments (DOE) is a statistical tool, the most important of TQM for the design of high quality at lower prices Taguchi Method provides an effective method and a system for optimizing the design for. Performance, quality and cost. The basic design stage trials traditionally are too complex and not easy to use. Many of the trials have to be carried out on a number of process parameters added. To solve this problem Taguchi method uses a special design of the array to study the parameter space that only a small number of trials. Taguchi is the developer of how Taguchi Method was widely used in engineering analysis and includes a plan of experiments with the aim of getting information in a controlled and to obtain information about the circumstances. of assignment process The greatest advantage of the method is to save the efforts in conducting trials. So you reduce the time trials as well as the costs by a factor quickly.

A. *Process Variables and their Limits*

First pilot experiments were done on the work piece using random values and then from those pilot experiments the suitable values of these parameters were selected. On the basis of observations from the pilot experiments these levels were found suitable for the experimentation.

Factors	**Units**	**Level-1**	**Level-2**	**Level-3**
Spindle Speed (N)	RPM	220	330	440
Feed (F)	Mm/Rev.	0.2	0.3	0.4
Depth Of Cut (DOC)	Mm	0.5	1	1.5

Table 1: Process variables and their limits.

B. *L9 Orthogonal Array*

Run	**C.S**	**Feed**	**D.O.C**

1	440	0.4	0.5
2	440	0.3	1
3	440	0.2	1.5
4	330	0.4	1
5	330	0.3	1.5
6	330	0.2	0.5
7	220	0.4	1.5
8	220	0.3	0.5
9	220	0.2	1

Table 2: Taguchi's L9 Orthogonal Array.

C. Material Removal Rate Measurement

Material removal rate (MRR) has been calculated from the difference of weight of work piece before and after experiment.

$$MRR = \frac{W_i - W_f}{\rho_s \, t} \quad mm^3/\min \text{ or } mm^3/sec.$$

D. Measurement of MRR

C.S	Feed	D.O.C	Time	Initial Wt.	Final Wt.	Reduction in Wt.	$(W_i - W_f)/\rho_s t$ in mm^3/ sec
440	0.4	0.5	11.16	282.5	276.86	5.64	65.63
440	0.3	1	16.13	288.51	278.26	10.25	82.53
440	0.2	1.5	23.8	288.8	264.44	24.36	132.93
330	0.4	1	16.59	285.88	277.6	8.28	64.82
330	0.3	1.5	23.87	279.96	265.2	14.76	80.31
330	0.2	0.5	32.4	285.52	272.66	12.86	51.55
220	0.4	1.5	24.67	284.96	268.65	16.31	85.86
220	0.3	0.5	31.19	284.74	279.49	5.25	21.86
220	0.2	1	44.65	281.59	280.3	1.29	3.75

Table 3: Measurement of MRR

E. Response Table for Means

Response Table for Means			
Level	**C.S**	**Feed**	**D.O.C**
1	37.16	62.74	46.35
2	65.56	61.56	50.37
3	93.70	72.10	99.70
Delta	56.54	10.54	53.35
Rank	1	3	2

Table 4: Response Table for Means

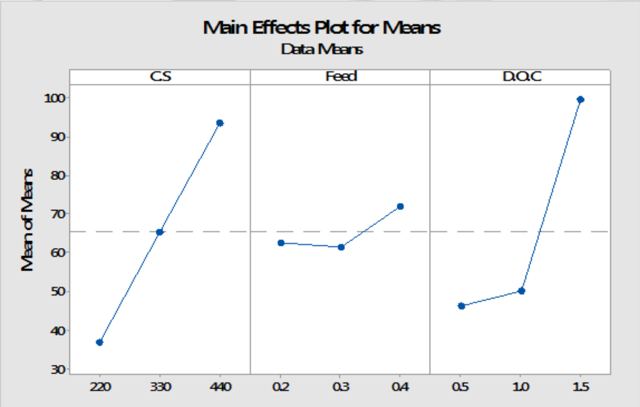

Fig. 1: Shows the effect of different parameters on MRR.

III. ANALYSIS

A. Analysis of Variance for Means

Source	DF	SeqSS	Adj SS	Adj MS	F	P
C.S	2	4794.8	4794.8	2397 .4	4.39	0.1 85
Feed	2	200.1	200.1	100. 1	0.18	0.8 45
D.O.C	2	5296.0	5296.0	2648 .0	4.85	0.1 71
Residual Error	2	1091.4	1091.4	545. 7		
Total	8	11382.3				

Table 5: Analysis of Variance for Means

IV. CONCLUSION

It is concluded that for MRR be maximum factor Cutting speed has to be at high level 3, Feed has to be at high level 3 & D.O.C has to be at high level 3. As shown in table below.

Physical Requirements	**Optimal Combination**		
	C.S	F	D.O.C
Maximum MRR	440	0.4	1.5
	Level-3	Level-3	Level-3

Table 5.1: Optimal combination for MRR

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